Towards Learned Color Representations for Image Splicing Detection

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Did these events really occur?

Images based on
MS COCO Database

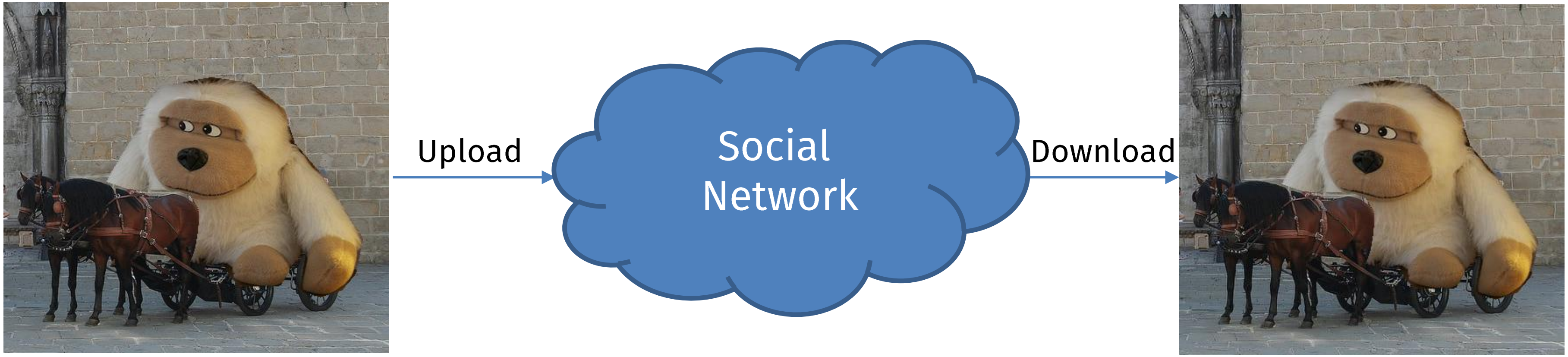
Multimedia Forensics – Goals and Methods

Important goal of multimedia forensics:
Determine authenticity of images

Typical approaches:
Exploit high frequent (HF) image statistics, e.g.

- Camera fingerprint
- Noise statistics
- Compression artifacts
- Resampling artifacts

The Impact of Social Networks



The Impact of Social Networks

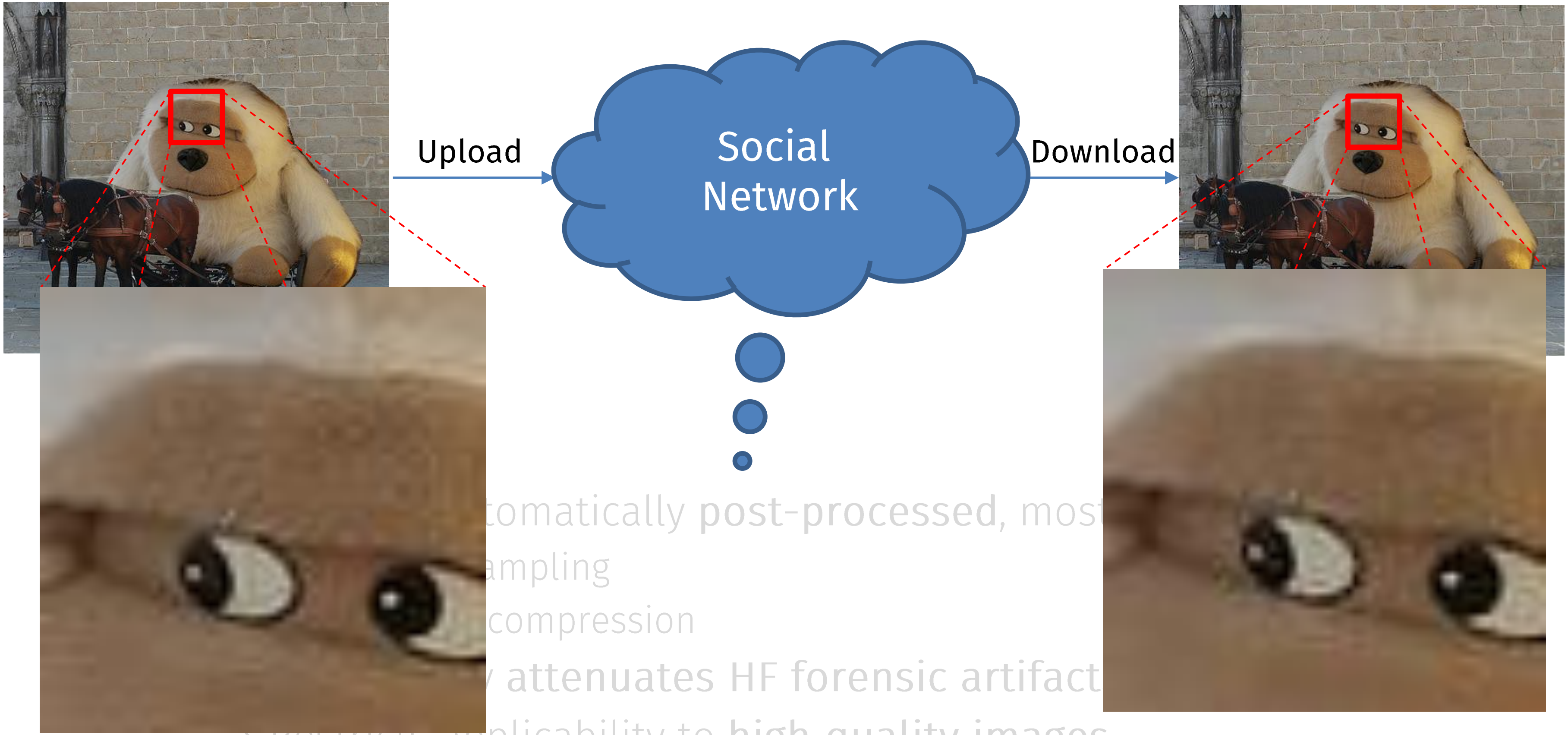
Images are automatically post-processed, most notably:

- Downsampling
- JPEG recompression

→ Significantly attenuates HF forensic artifacts

→ Restricts applicability to high quality images

The Impact of Social Networks



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Towards Robust Manipulation Detection

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We explore a novel cue based on the color formation of an image

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Can we detect manipulations **independently of the image quality**?

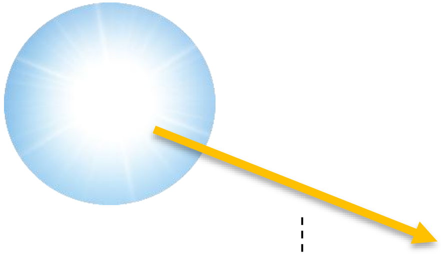
Physics-based cues are often **remarkably robust** against post-processing

We explore a **novel cue** based on the **color formation** of an image

Images based on MIT-Adobe 5k Database

Background: Color Image Formation

Light source

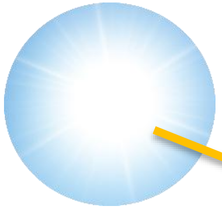


Spectral illuminant density: $e(\lambda)$

$e(\lambda)$

Background: Color Image Formation

Light source



Spectral illuminant density: $e(\lambda)$

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Scene

Spectral reflectance: $r(\lambda)$

$e(\lambda) \cdot r(\lambda)$

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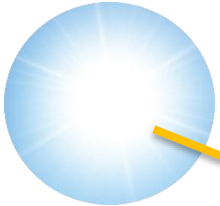

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Camera

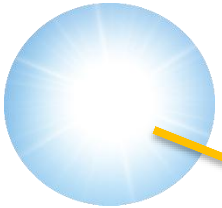
In-camera processing

- Camera sensitivity: $\vec{c}\,(\lambda)$
- White balancing
  Color transformation
  etc.

(White balancing, Color transformation, etc.) } Ω

Background: Color Image Formation

Light source	Scene	Camera	Color image



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(White balancing, color transformation, etc. $\}\ \Omega$)

$e(\lambda)$

$e(\lambda) \cdot r(\lambda)$

$$\Omega\left(\int_{\Lambda} e(\lambda) \cdot r(\lambda) \cdot \vec{c}(\lambda)\, d\lambda\right)$$

Proposed Method: Idea

$$\vec{I} = \boldsymbol{\Omega}\left(\int_{\Lambda} \mathbf{e}(\boldsymbol{\lambda}) \cdot r(\lambda) \cdot \vec{\mathbf{c}}(\boldsymbol{\lambda})\, d\lambda\right)$$

e: illuminant sp. density
Ω: in-camera processing
$\vec{c}$: sp. camera sensitivity
r: spectral reflectance
$\vec{I}$: image intensity

$\mathbf{e}$, $\boldsymbol{\Omega}$ and $\mathbf{c}$ characterize imaging conditions

Assume consistency of $\mathbf{e}$, Ω and $\mathbf{c}$ in pristine image

Image source: NUS Database

Proposed Method: Idea

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⬇

How can we control the spectral reflectance $\mathbf{r}(\lambda)$?

Image source: NUS Database

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How can we control the spectral reflectance $\mathbf{r(\lambda)}$?

⬇

Place Macbeth ColorChecker in image

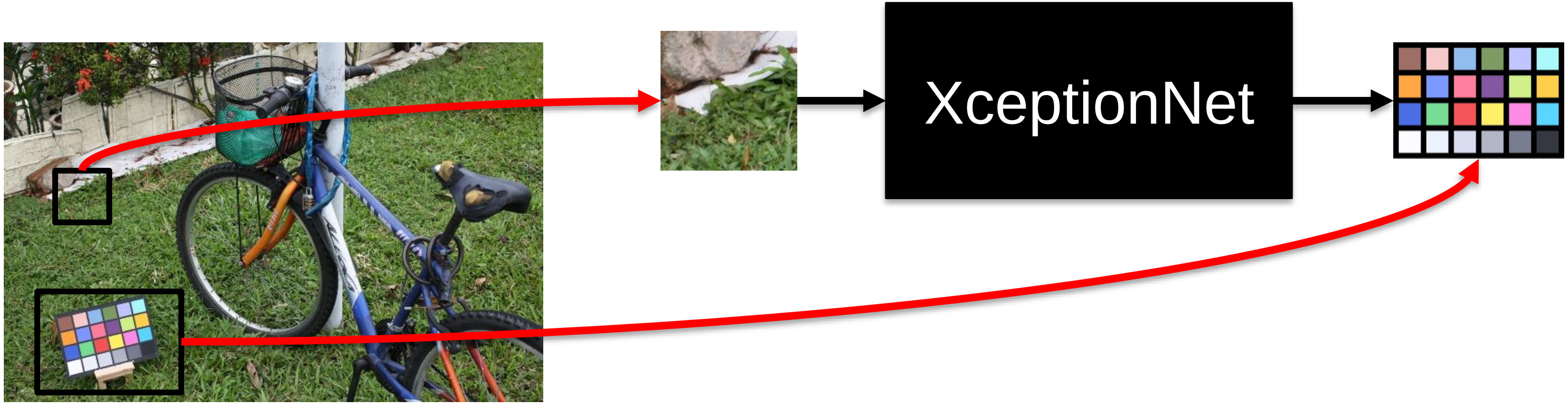
Image source: NUS Database

Proposed Method: Learning the Color Descriptor

1. Train a CNN to locally estimate the observed colors of the ColorChecker

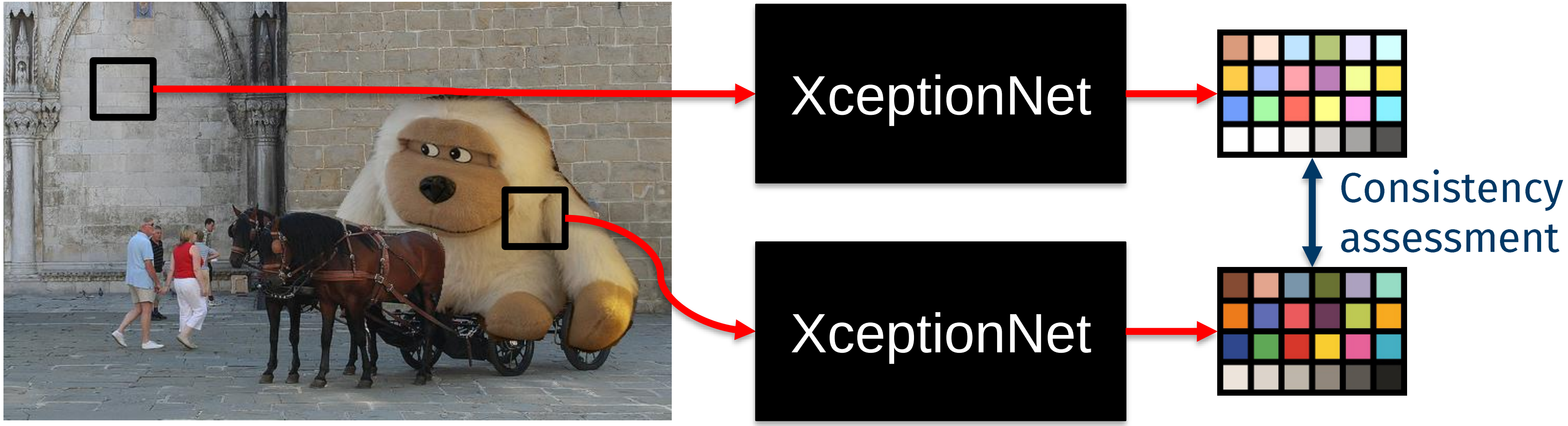
The learned color descriptor is

- Covariant with respect to imaging conditions
- Invariant with respect to reflectance of the image patches



Proposed Method: Consistency Assessment

2. Classify consistency of local estimates



Discriminability of the Learned Color Descriptor

How well do the learned color features characterize the image provenance of a patch?

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How well do the learned color features characterize the image provenance of a patch?

- Extract non-overlapping patches from test images
- Randomly split patches into training / test set
- Train a Random Forest to classify patch provenance: “From which image is this patch?”
- Repeat for increasingly stronger compressions

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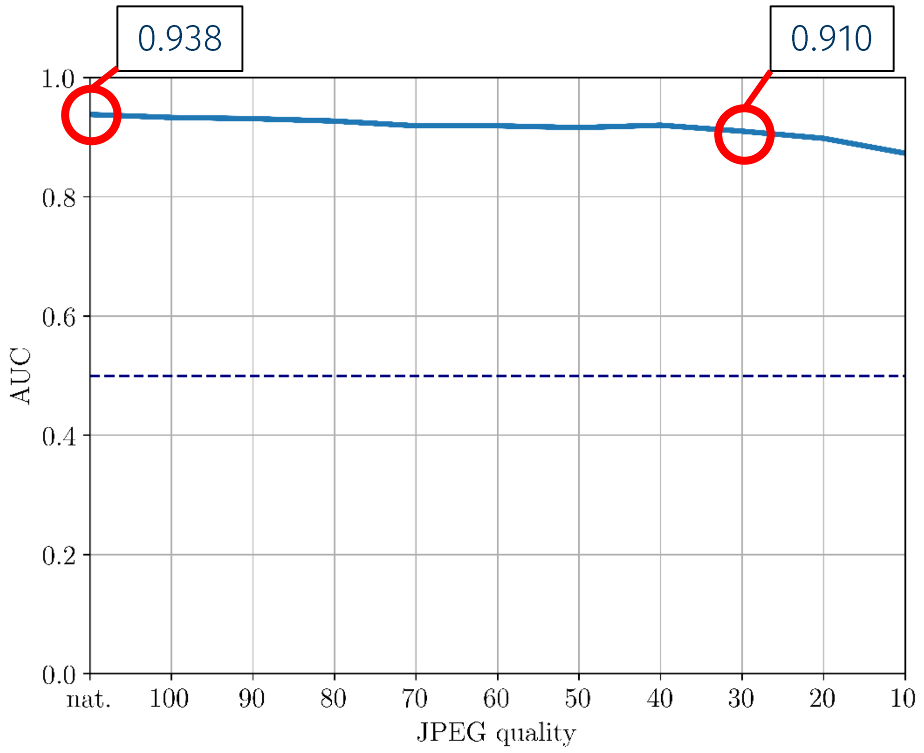

Consistency Assessment with the Color Descriptor

A more realistic scenario: Are different regions in an image consistent?

Image based on Dresden Image Database

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- Training on VISION Database,
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- Test splices: combine same scene
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Image based on Dresden Image Database

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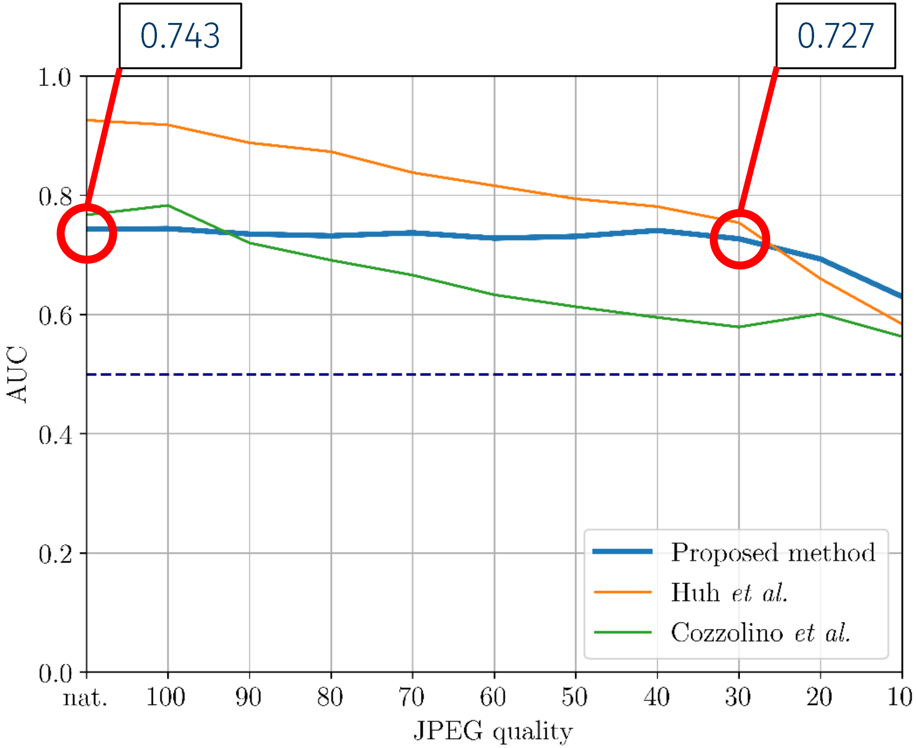

Huh *et al.*: *"Fighting Fake News: Image Splice Detection via Learned Self-Consistency"*, ECCV '18
Cozzolino *et al.*: *"Splicebuster: A new blind image splicing detector"*, WIFS '15

Outlook: Qualitative Results

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Outlook: Qualitative Results (*cont.*)

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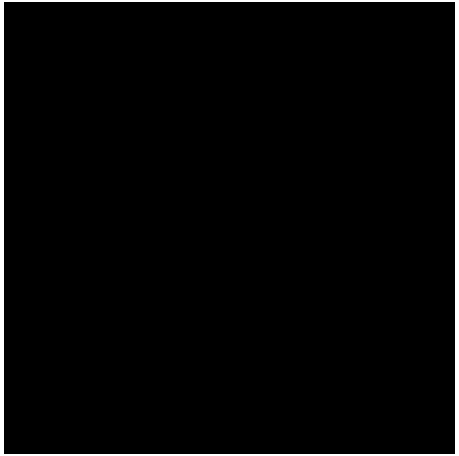

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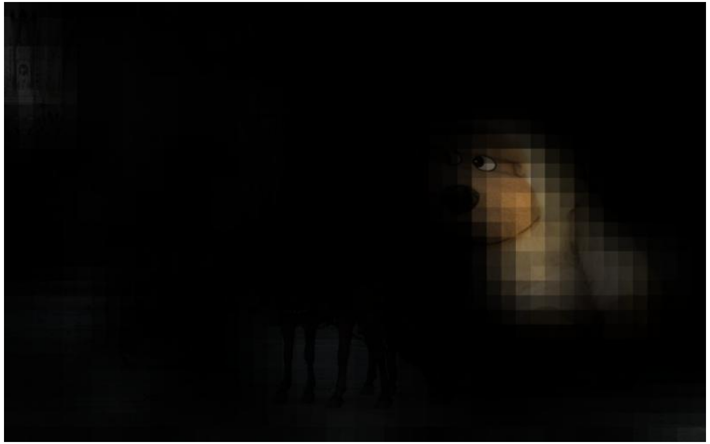

Summary

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Conclusion

- We presented a novel cue based on color image formation
- We demonstrated remarkable robustness against JPEG compression
- Promising to work in low-quality settings

Ongoing work

- Incorporate prior knowledge on camera
- Perform consistency assessment using Siamese network

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Thank you!

Questions?